Site characterization using joint reconstruction of disparate data types



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Site characterization, CO₂ storage, and risk assessments are underlain by geological uncertainty

What is the geological uncertainty?

Are there fast-paths in the reservoir?

Does a fault transmit fluids or segment a reservoir into compartments?

- How can one integrate data streams to understand reservoir performance?
- Can one reduce uncertainty?

 How can 4D seismic, injection
 volumes, and production data
 constrain uncertainty

In Salah Project, Kretchba field



From Rittiford et al., 2004

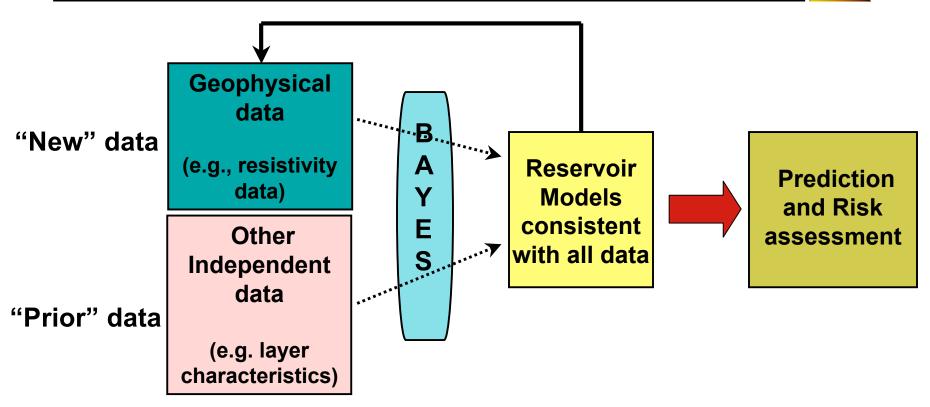
Method for the subsurface imaging of reservoirs and CO₂ plumes



- Monte Carlo Markov chain (MCMC):
 - uses disparate data types: integration of data
 - Core logs, geophysical logs, injected CO₂ volume
 - Formation geostatistical trends: correlation length, thickness & juxtapositional tendencies
 - Production data, tracer results, surface & cross-borehole geophysics
- Provides rigorous measure of uncertainty in the subsurface
 - Minimization of CO₂ storage risks requires knowledge of subsurface uncertainty
 - Unknown reservoir properties, measurement error, lack of sensitivity/resolution of geophysics
- The output is distribution of likely reservoir models
 - Alternative models ranked based on how well they fit the data

MCMC is a stochastic inversion & data integration approach



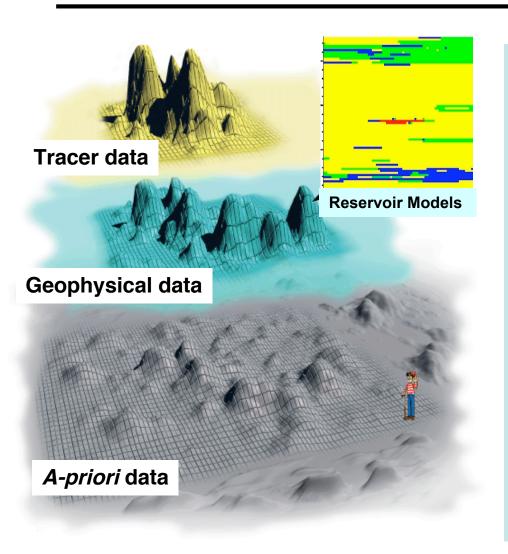


The benefits are:

- Rigorously combine geologic & geophysical insight with measurements,
- Measures uncertainty in complex problems,
- Robust noisy data, solution space with multiple local minima

Goal is to find reservoir models that are consistent with all available data





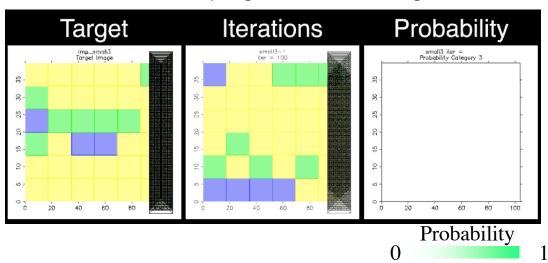
- Most methods look for the "best" answer
 - -model at the top of the tallest hill
 - Geophysical inversion is typically non-unique
- · MCMC:
 - Identifies alternative models
 - Alternatives are objectively ranked (hill height)
 - Measures variability (hill width)
- Joint reconstruction of multiple data increases the height of a few hills
 - Uses cascade reconstruction approach (Mosegard & Tarantola, 1995)
 - -Reduce uncertainty

Importance Sampling to the Rescue: Rapid Searching of the Good Matches



Random Sampling of Possible Configurations

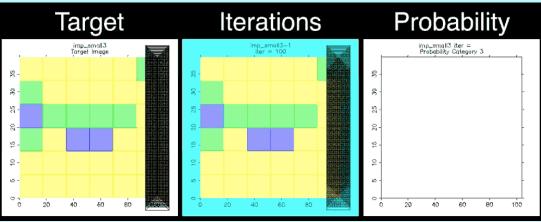
When only random Monte Carlo sampling is used, the true configuration is not found in 700,000 iterations. (20 trillion possible)



The stacked sum of random configurations is equal to the prior probability, or the information built into the original lithology model.

MCMC Sampling of Possible Configurations

With importance sampling, the engine repeatedly finds the true configuration (iterations with blue).



The accepted configurations are summed (stacked) to give the posterior probability including error in data and models.

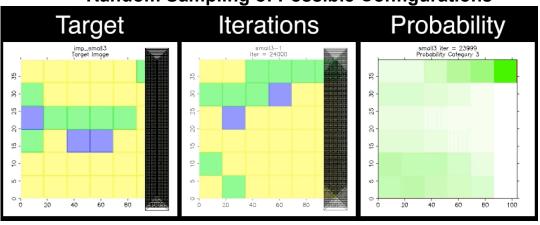
The most probable configuration is repeatedly identified.

Importance Sampling to the Rescue: Rapid Searching of the Good Matches



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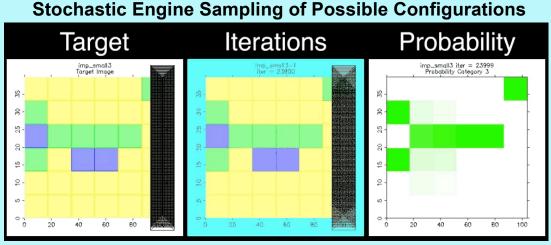


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Probability 0

1

With importance sampling, the engine repeatedly finds the true configuration.

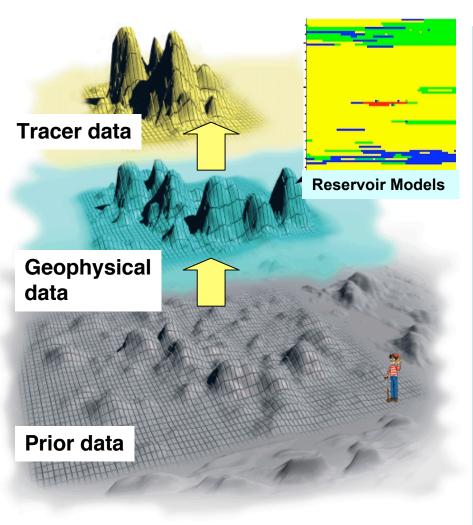


The accepted configurations are summed (stacked) to give the posterior probability including error in data and models.

The most probable configuration is repeatedly identified.

MCMC finds models that are most consistent with the available data

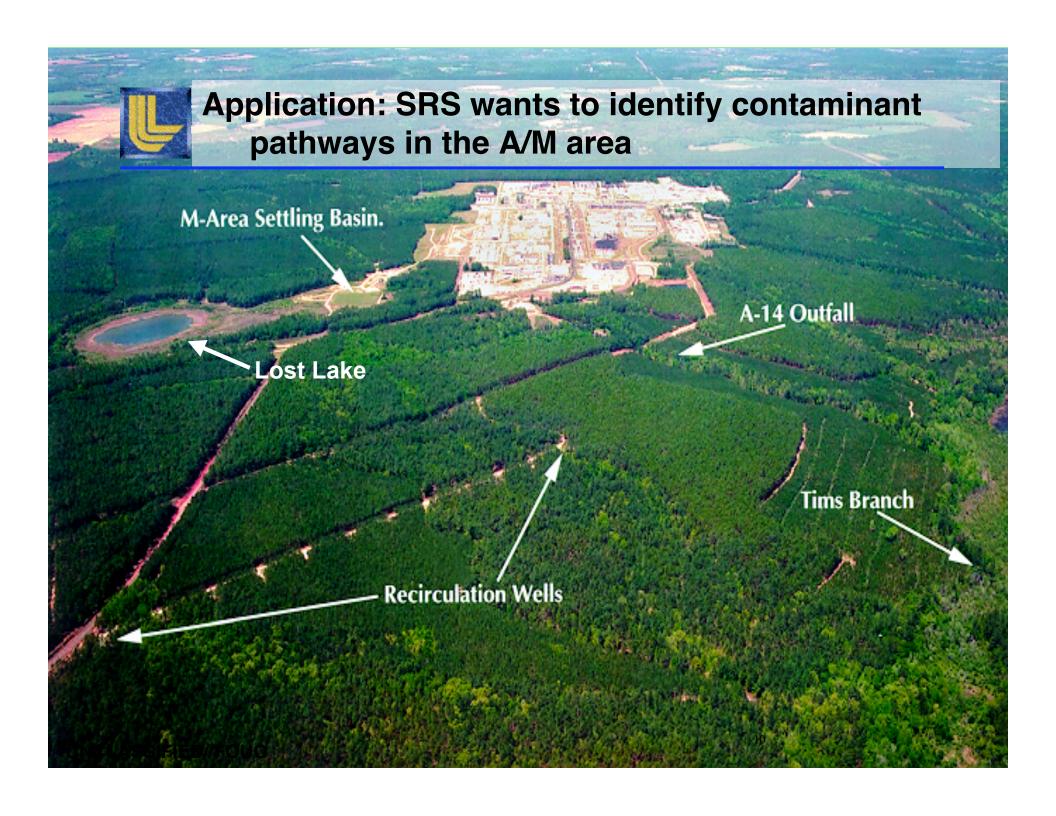




- Prior data: existing core or welllogs, 3-D seismic, formation geostatistical trends, etc.
- Other data could be geophysical measurements, production data, tracer results, etc.
- •Tends to hover in regions where models best fit data
 - used to rank alternatives
 - much more efficient than conventional Monte Carlo
- Samples the whole space of possible models
 - needed to quantify uncertainty
 - different from simulated annealing multiple answers
 - computationally intensive



MCMC applied to reservoir characterization

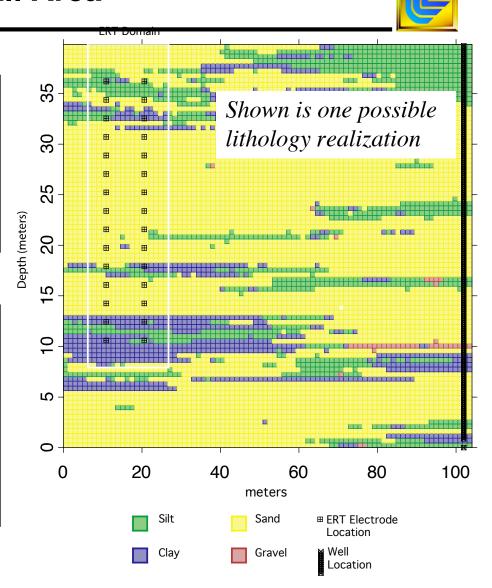


We tested MCMC with data from the Savannah River Site A/M Outfall Area

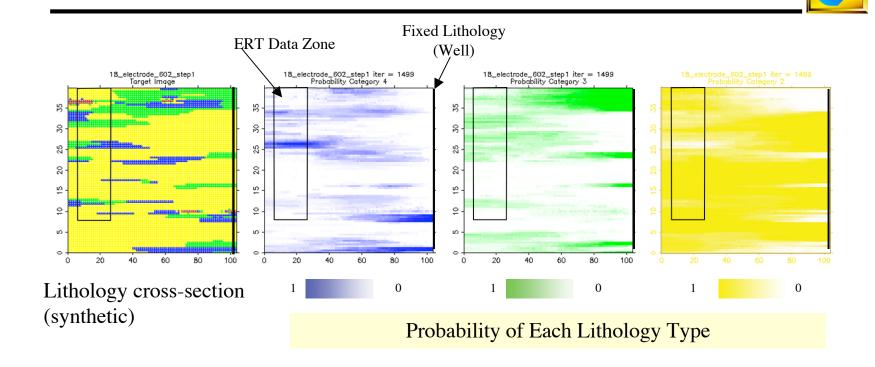
- Geostatistical Model (Carle et al.) used to generate models
 - Uses borehole data & geospatial trends
 - Correlation lengths, thickness and juxtaposition

• Knowns:

- -Lithology at distal well
- Overall site lithologic trends
- ERT Data in two wells (poor quality)
- · Unknowns:
 - Reservoir model away from distal well

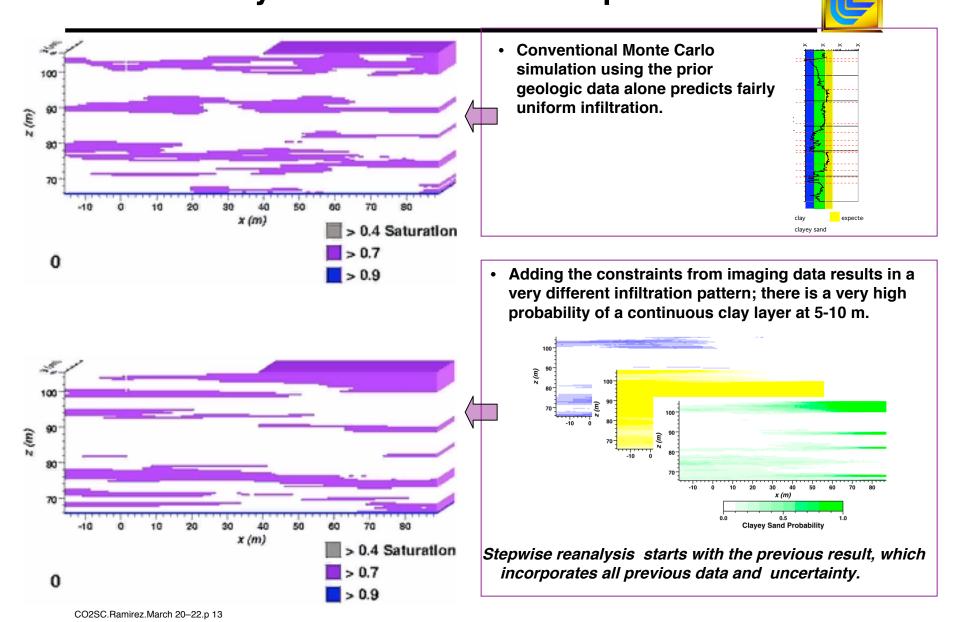


The search found the most likely reservoir models

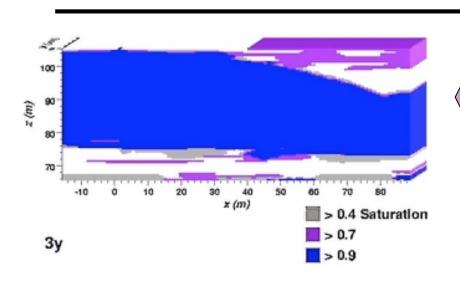


Result: quantitative assessments of uncertainty: useful for risk assessment and site characterization.

Infiltration at the SRS outfall site: the *most likely* differs dramatically from conventional expectation

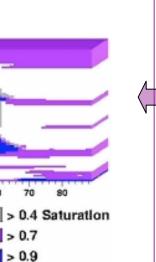


Infiltration at the SRS outfall site: the *most likely* differs dramatically from conventional expectation



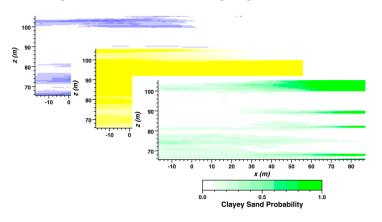
x(m)

 Conventional Monte Carlo simulation using the prior geologic data alone predicts fairly uniform infiltration.



 Adding the constraints from imaging data results in a very different infiltration pattern; there is a very high probability of a continuous clay layer at 5-10 m.

clayey sand



Stepwise reanalysis starts with the previous result, which incorporates all previous data and uncertainty.

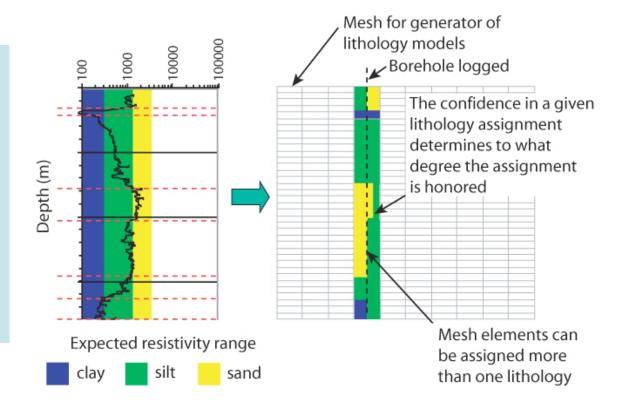
z (m)

34

Lithology and geophysical logs are used to constrain the lithology models



- Bayesian time-series analysis is applied to establish confidence levels for given lithology types.
- This type of "soft" conditioning allows many kinds of data to be incorporated

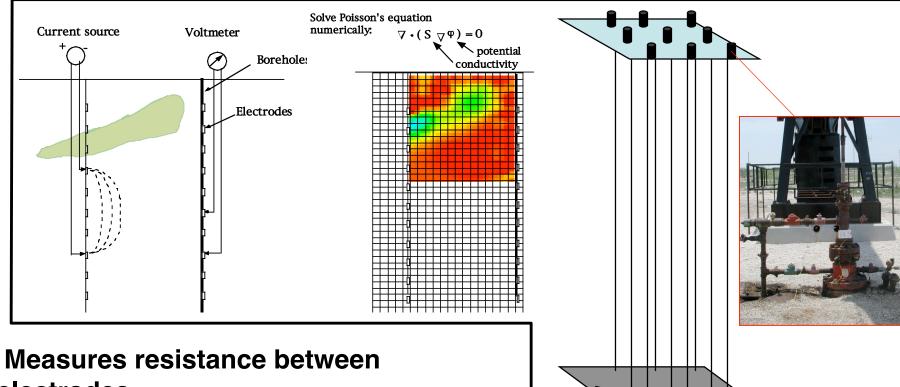




MCMC applied to CO₂ plume monitoring

Electrical resistance measurements detect changes in pore fluid resistivity





electrodes

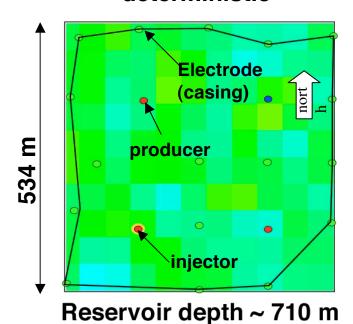
Short electrodes on casing surface of production/injection wells

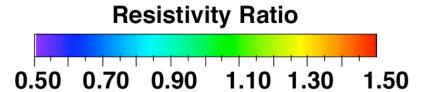
Borehole casings = long electrodes Fast, cheap, low signal to noise Horizontal resolution only

We have monitored CO₂ injection at the Salt Creek Field, Wyoming



deterministic



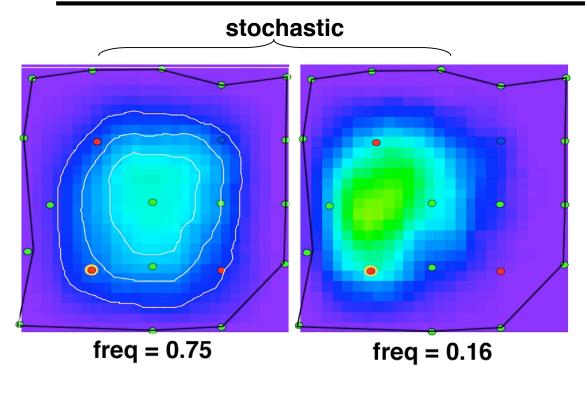


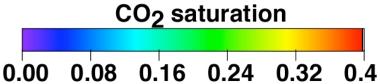
- Used abandoned well casings as long electrodes
 - ~ 710 m deep
- Time-lapse results using deterministic approach were discouraging
- Poor signal to noise
 - ~4% of casing length in contact with reservoir

Thanks to RMOTC and Anadarko Petroleum for their support

Time-lapse stochastic inversions offered some hope





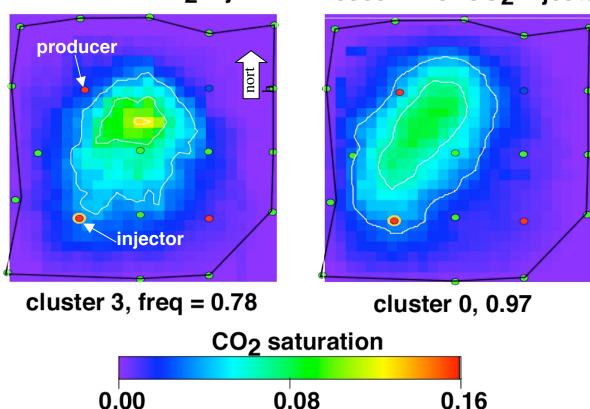


- Most frequent result is donut-shaped
 - Modeling suggests that this is consistent with poor signal to noise data
- Less frequent results show a plume starting at the injection
- Decided to use injected CO₂ volume as an additional constraint

Time-lapse sequence shows a growing CO₂ plume







- Injected volume data helps pull out the small changes caused by the CO₂
- Confidence in the result improves when CO_2 inj. volume data is used
- Fast path established between injector and producer

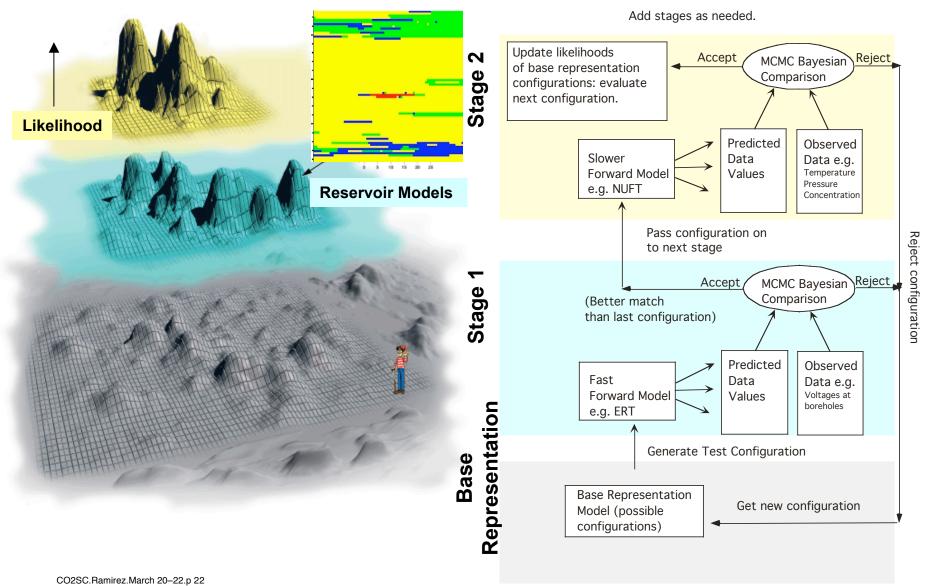
MCMC can be used for site characterization and plume monitoring



- Joint reconstruction of disparate data types
- Can handle noisy data, inversions with many local minima
- Computationally intensive
 - Almost all the time is spent on the forward problem
 - Requires parallel clusters with 10's to 100's of nodes for these applications
- Models can be used for risk evaluation, identify range of reservoir performance, identify CO₂ flowpaths
- Provides rigorous measure of uncertainty in the subsurface

The Monte-Carlo Markov-Chain approach finds models consistent with all available data





Many geophysical inversions are ill-posed, non-linear, non-unique



- Geophysical inversion is typically unstable, requires constraints
- Classical (deterministic) approach requires Tikhonov-type regularization for stability (e.g., minimum roughness)

$$F(m) = \|D_{cal}(m) - D_{obs}\|_{w}^{2} + \alpha R(m)$$

- Statistical inversions are stabilized by a priori information
 - When enough information (constraints) added, problem is wellbehaved (no longer ill-posed)
 - Prior information serves the same purpose as the regularization functional

$$\sigma(m) = k \rho(m) L(m) \qquad F(m) = \left\| D_{cal}(m) - D_{obs} \right\|_{w}^{2} + \alpha R(m)$$